Super-Resolution OCT Based on α-Stable Distributions and Sparse Representations

Daniel Valdez Zermeno, Perla Mayo, Lindsay Nicholson, and Alin Achim
University of Bristol, UK

Abstract—**We present a new approach to single-image super-resolution in Optical Coherence Tomography (OCT) images. Indeed, although OCT is the one in-vivo retinal imaging modality offering the highest resolution, this is still far below what microscopy techniques can achieve, albeit ex-vivo. In this work we investigate a non-convex regularization technique using a multivariate generalization of the minimax-concave (GMC) scheme and a forward-backward splitting (FBS) algorithm. Based on the observation that sparse representations of OCT images are heavy-tailed, an α-stable dictionary is employed. The resulting algorithm is tested on real OCT retinal images of murine eyes. Significant deblurring and general quality enhancement is noticed and in most cases our method provides the best results both objectively and subjectively.**

I. Introduction

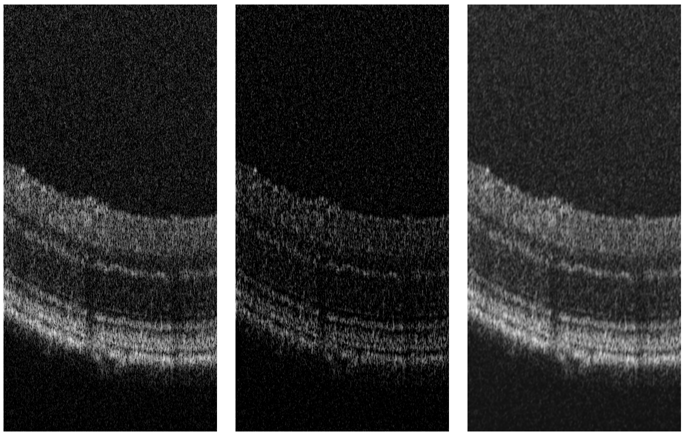
OCT is an in-vivo non-invasive technique that uses light in order to image structures inside the eye. One of the main structures imaged with this technique is the retina, which is a highly organised tissue in which light sensing cells and nerve fibre that carry signals from them to the brain are organised in distinct layers [1]. Direct visualisation of the retina has thus played an increasingly central role in the assessment and management of many diseases both local to the eye (e.g. glaucoma, macular degeneration) and systemic (e.g. type I and type II diabetes) [2]. Nevertheless, because of the limited resolution, these are generally detected in advanced stages. Several post-processing techniques aimed at increasing image resolution have thus been developed. This work proposes a super-resolution (SR) scheme based on dictionary learning using α-stable models and convex regularization.

II. Proposed method

Based on the observation that sparse representations of OCT images are heavy-tailed, this work employs a dictionary learning method that makes use of α-stable distributions as prior for the data. The approach has been coined by its authors as “SparseDT” and is presented in details in [3]. Based on the SparseDT representation, our proposed SR method is designed to perform convex regularization via a multivariate generalisation of the minimax-concave (GMC) scheme [4] within a forward-backward splitting (FBS) algorithm. The advantage of a GMC penalty over the common l_1 norm is that it allows for enforcing a sparser solution, while at the same time preserving the convexity of the overall cost function. The cost function to be optimized when using a GMC penalty is:

$$F(\boldsymbol{x}) = \frac{1}{2}\,\|\boldsymbol{y} - A\mathbf{x}\|_2^2 + \lambda\psi_b(\boldsymbol{x}) \quad (1)$$

Since we solve a super-resolution problem, the matrix A should effectively be equal to $\boldsymbol{SH}$, where $\boldsymbol{S}$ is the down sampling operator and $\boldsymbol{H}$ is the point spread function (PSF) of the OCT system. One should note that the upscaling of the image is not done as part of the convex optimization; instead the image is interpolated before the patch extraction step of our algorithm. Subsequently, the optimization algorithm performs only the deconvolution by recovering the sparse vectors of coefficients. Hence, in our implementation we actually have $A = \boldsymbol{HD}$, where $\boldsymbol{D}$ is the dictionary.



(a) (b) (c)

Fig. 1: Results on real OCT image (a) Original (512 x 1024) (b) ADMM with TV denoiser (1024x2048) (c) FBS with GMC using α-stable dictionary (1024x2048)

III. Results and discussion

The proposed algorithm was evaluated using retinal OCT images of murine eyes. The dictionary is trained using 60 images from our dataset. The results were compared to other single image SR algorithms applied to OCT. For illustrative purposes, in Fig. 1 we show comparison to a method involving a TV-norm and ADMM optimization, implemented in the spatial domain. For most of the images we have tested, the proposed algorithm provided superior results. The retinal layers are more easily distinguishable in general. Nevertheless, in images where the content was too noisy or the retinal layers too disrupted, the algorithm achieves improved image quality but to a lesser degree.

References

[1] M. D. Abramoff, M. K. Garvin, and M. Sonka, “Retinal imaging and image analysis,” *IEEE Reviews in Biomedical Engineering*, vol. 3, pp. 169–208, 2010.

[2] N. Anantrasirichai, L. Nicholson, J. E. Morgan, I. Erchova, K. Mortlock, R. V. North, J. Albon, and A. Achim, “Adaptive-weighted bilateral filtering and other pre-processing techniques for optical coherence tomography,” *Computerized Medical Imaging and Graphics*, vol. 38, no. 6, pp. 526 – 539, 2014.

[3] P. Pad, F. Salehi, E. Celis, P. Thiran, and M. Unser, “Dictionary learning based on sparse distribution tomography,” in *International Conference on Machine Learning*, 2017, pp. 2731–2740.

[4] I. Selesnick, “Sparse regularization via convex analysis,” *IEEE Transactions on Signal Processing*, vol. 65, no. 17, pp. 4481–4494, 2017.